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Determination of Optimal Parameter in Deep Drawing Process by Using Fuzzy Logic Method

Authors

Pawan Ashok Ghormode¹, Prof N K Kamble², Prof S S Sarnobat³

¹M.E. Production Dept. Engg Dr D Y Patil College of Engg Akurdi Pune

^{2,3}Professor Production Dept Engg Dr D Y Patil College of Engg Akurdi, Pune

Abstract

Fuzzy logic is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple fuzzy logic is a more intuitive approach without the far-reaching complexity. This paper discusses flexible approaches for fuzzy optimization problems. Specifically, it presents a new solving method in deep drawing process. It is helpful for determine optimal combination of process parameters.

Keywords: *fuzzy optimization, flexible approaches, fuzzy multiple objective decision making,*

1. INTRODUCTION

In recent years, the number and variety of applications of fuzzy logic have increased significantly. The precise quantification of many system performance criteria and parameter and decision variables is not always possible, nor is it always necessary. When the values of variables cannot be precisely specified, they are said to be uncertain or fuzzy. If the values are uncertain, probability distributions may be used to quantify them. The point of fuzzy logic is to map an input space to an output space, and the primary mechanism for doing this is a list of if-then statements called rules. All rules are evaluated in parallel, and the order of the rules is unimportant. The rules themselves are useful because they refer to variables and the adjectives that describe those variables.

2. METHODOLOGY

Methodology is nothing but systematic way, in which theoretical analysis of the methods applied to almost every field of study, or it is the theoretical analysis of the body of methods associated with a branch of knowledge. The concepts are generally classified in paradigm, theoretical model, phases and quantitative or qualitative techniques.

A Methodology is not providing a solution but it is used to solve a problem theoretically, are called as “best practices”

2.1 Initial Grey Relational Analysis for FUZZY optimization

The GRA theory was invented in 1982 by Deng. Grey analysis then comes to as a clear set of statements about system solutions. At one extreme no solution can be defined for a system with any information. At the other extreme a system with perfect information has a unique solution; in the middle GRA gives the variety of variable solutions. Grey analysis does not attempt to find the best solution, but does provide techniques for determining the best solutions.

The procedure of Grey relational analysis are as follow:

Step 1: Data Normalizing Process

The first step in grey relational analysis is data preprocessing which performed to prepare raw data for the analysis where the original sequence is transferred to a comparable sequence between zero and unity which is also called as the grey relational generation. In this investigation “smaller-the-better” criterion is used for normalization of all the responses as.

$$x_i^*(k) = \frac{\max x_i^{(0)}(k) - x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)}$$

Step 2: Determination of deviation sequence

The deviation sequence $\Delta 0_i(k)$ is the absolute difference between the reference sequence $x_0^*(k)$ and the comparability sequence $x_i^*(k)$ after normalization. It is determined using Eq.

$$\Delta 0_i(k) = |x_0^*(k) - x_i^*(k)|$$

Step 3: Determination of Grey Relational Coefficient

GRC for all the sequences expresses the relationship between the ideal (best) and actual normalized S/N ratio. If the two sequences agree at all points, then their grey relational coefficient is 1. The grey relational coefficient $\gamma(x_0(k), x_i(k))$ can be expressed by Eq.

$$\gamma(x_0(k), x_i(k)) = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta 0_i(k) + \zeta \Delta_{max}}$$

Where, Δ_{min} is the smallest value of $\Delta 0_i(k) = \min_i \min_k |x_0^*(k) - x_i^*(k)|$ and Δ_{max} is the largest value of $\Delta 0_i(k) = \max_i \max_k |x_0^*(k) - x_i^*(k)|$, $x_0^*(k)$ is the ideal normalized S/N ratio, $x_i^*(k)$ is the normalized comparability sequence, and ζ is the distinguishing coefficient. The value of ζ can be adjusted with the systematic actual

need and defined in the range between 0 and 1; here it is taken as 0.5.

Step 4: Determination of Grey Relational Grade

$$\gamma(x_0, x_i) = \frac{1}{m} \sum_{i=1}^m \gamma(x_0(k), x_i(k))$$

The overall evaluation of the multiple performance characteristics is based on the grey relational grade. The grey relational grade is an average sum of the grey relational coefficients.

2.2 Fuzzy adaptive control deep-drawing process.

The control system consists of the fuzzy inference and the database. The following five variables were captured/sensed online during the process: Punch force, blank holding pressure, major strain, minor, and Thickness reduction. The fuzzy rule is constructed by the evaluation functions in the database. In this study, which is finding the influencing parameter are chosen objective function.

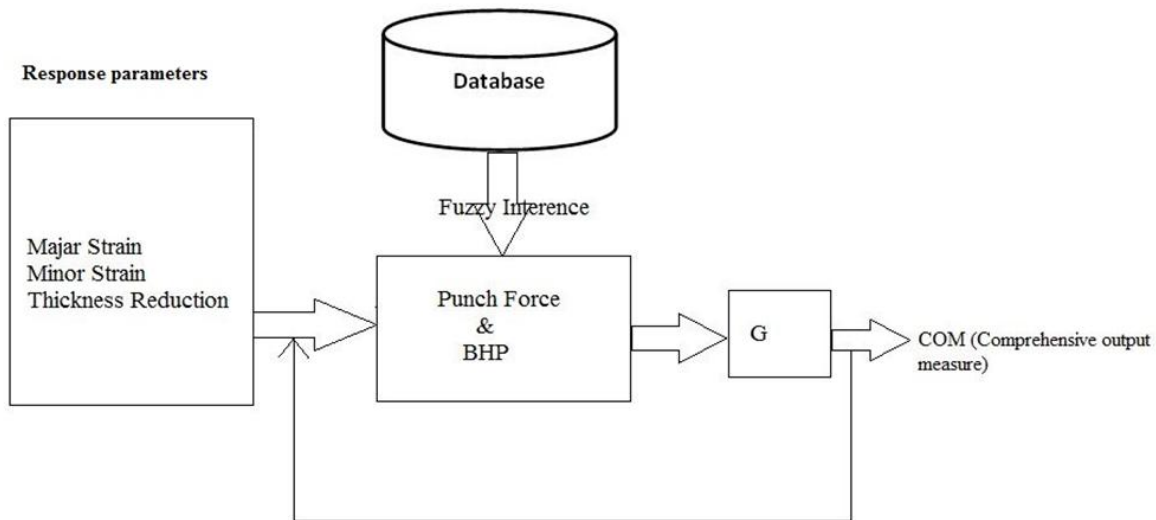


Fig 3.1: Block diagram of fuzzy adaptive control for the deep-drawing process

The fuzzy rule can be automatically produced by the membership function and if-then rules obtained from the database. To confirm the capability of the developed system, the effects of the combination of Punch force and BHP fuzzy

control on Thickness distribution, Major strain and minor strain are examined.

3. Experimental results and discussion

Table 3.1: Array details and Grey relational normalization

Sr.no.	Punch force (Ton)	Blank holding (Bar)	Major strain (%)	Minor Strain (%)	Thickness Reduction (%)	Normalized Data		
1	16	10	56.701	-20.125	20.561	0.0545	0.6946	0.0670
2	14	10	54.652	-19.413	19.641	0.4000	0.5633	0.2533
3	16	8	55.681	-19.156	20.298	0.2265	0.5159	0.1203
4	16	12	57.001	-21.782	20.892	0.0039	1.0000	0.0000
5	12	8	51.094	-16.357	15.954	1.0000	0.0000	1.0000
6	12	12	54.756	-17.624	17.025	0.3825	0.2335	0.7831
7	14	12	57.024	-20.264	19.785	0.0000	0.7202	0.2242
8	14	8	53.894	-18.486	18.756	0.5278	0.3924	0.4326
9	12	10	53.102	-18.089	18.121	0.6614	0.3193	0.5612

Table 3.2: Calculation of Deviation Sequence, GRC, GRD

Sr. no.	Deviation Sequence			Grey Relational Coefficients (GRC)			GRG
1	0.9455	0.3054	0.9330	0.3459	0.6208	0.3489	0.4385
2	0.6000	0.4367	0.7467	0.4545	0.5338	0.4011	0.4631
3	0.7735	0.4841	0.8797	0.3926	0.5081	0.3624	0.4210
4	0.9961	0.0000	1.0000	0.3342	1.0000	0.3333	0.5558
5	0.0000	1.0000	0.0000	1.0000	0.3333	1.0000	0.7778
6	0.6175	0.7665	0.2169	0.4474	0.3948	0.6975	0.5132
7	1.0000	0.2798	0.7758	0.3333	0.6412	0.3919	0.4555
8	0.4722	0.6076	0.5674	0.5143	0.4514	0.4684	0.4781
9	0.3386	0.6807	0.4388	0.5962	0.4235	0.5326	0.5174

3.1 Comprehensive output measure (COM) for GRG for each experiment

The Rule Viewer displays a roadmap of the whole fuzzy inference process. It is based on the fuzzy inference diagram described in the below section. See the single figure window with 25 plots nested in it. The three plots across the top of the figure represent the antecedent and consequent of the first rule. Each rule is a row of plots, and each column is a variable. The rule numbers are displayed on the left of each row. You can click on a rule number to view the rule in the status line.

- The first three columns of plots (the 18 yellow plots) show the membership functions referenced by the antecedent, or the if-part of each rule.
- The fourth column of plots (the six blue plots) shows the membership functions referenced by the consequent, or the then-part of each rule.
- The seven plot in the third column of plots represents the aggregate weighted decision for the given inference system.

Experiment: 1

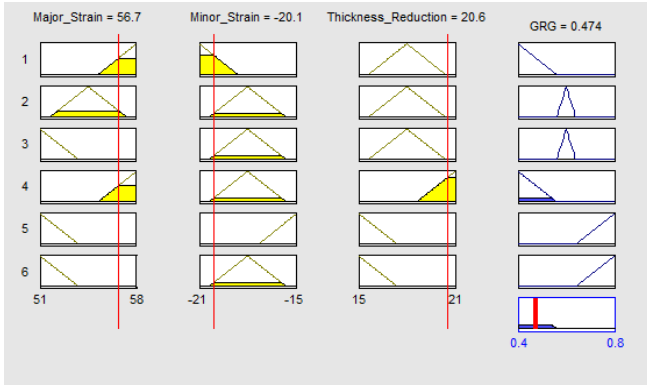


Fig3.1.1:- Ruler view display for experiment 1

Experiment: 5

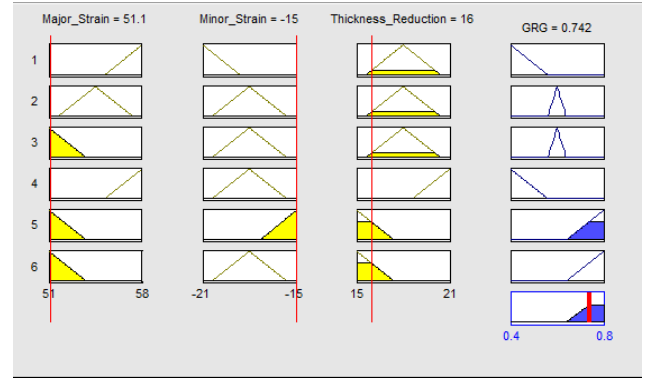


Fig3.1.5:- Ruler view display for experiment 5

Experiment: 2

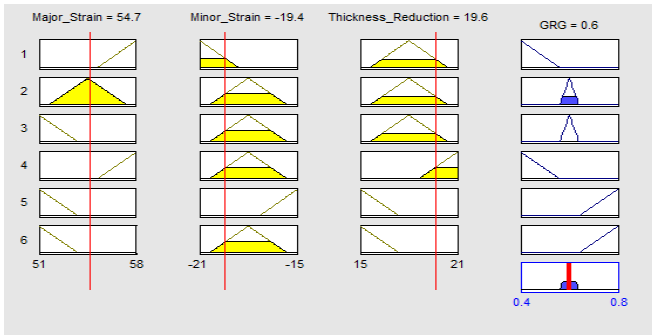


Fig3.1.2:- Ruler view display for experiment 2

Experiment: 6

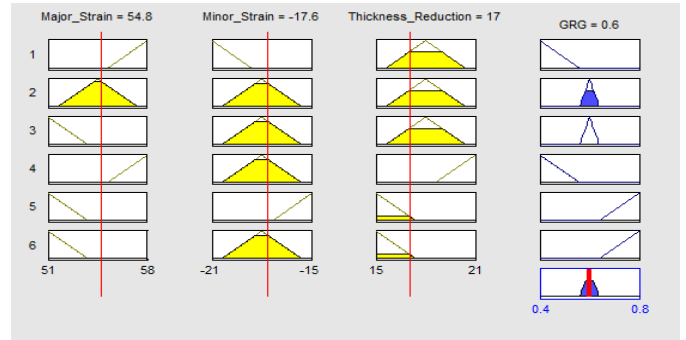


Fig3.1.6:- Ruler view display for experiment 6

Experiment: 3

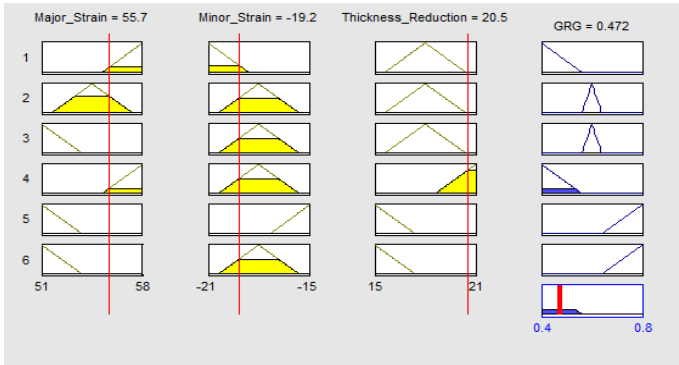


Fig3.1.3:- Ruler view display for experiment 3

Experiment: 7

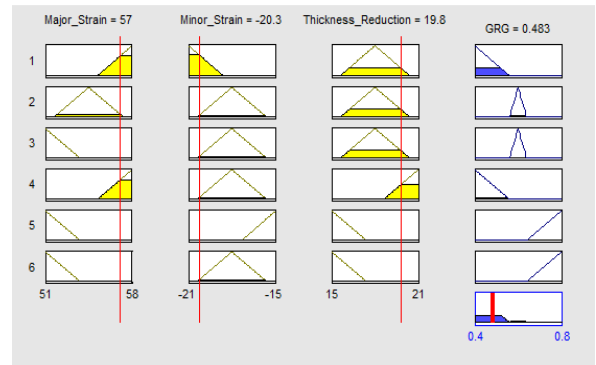


Fig3.1.7:- Ruler view display for experiment 7

Experiment: 4

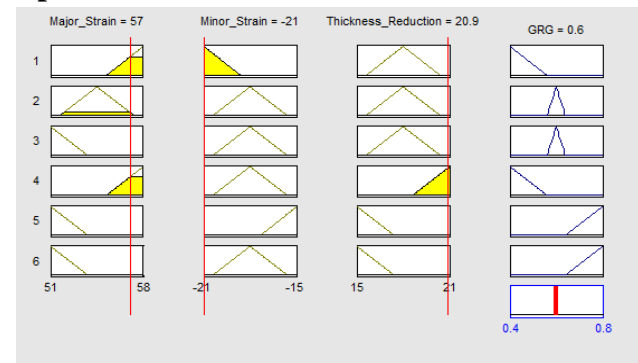


Fig3.1.4:- Ruler view display for experiment 4

Experiment: 8

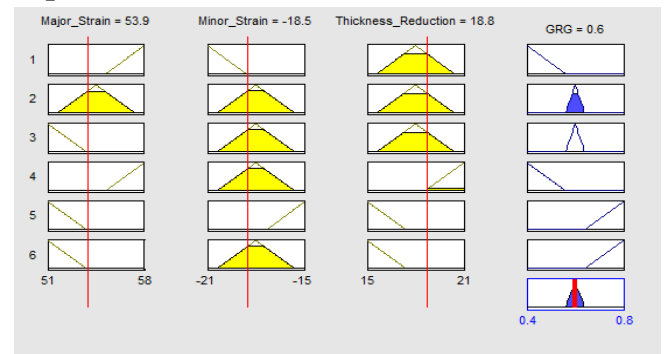


Fig3.9:- Ruler view display for experiment 8

Experiment: 9

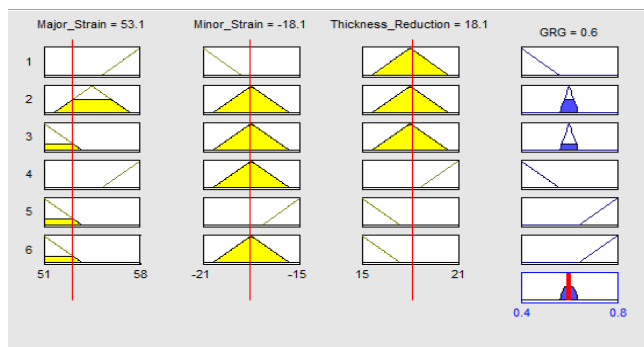


Fig3.1.9:- Ruler view display for experiment 9

3.2. Final comprehensive output measure (COM)

Table 3.2.1: - Final result COM output

Sr. no.	Punch force (Ton)	Blank holding (Bar)	Major strain (%)	Minor Strain (%)	Thickness Reduction (%)	comprehensive output measure (COM)
1	16	10	56.701	-20.125	20.561	0.474
2	14	10	54.652	-19.413	19.641	0.601
3	16	8	55.681	-19.156	20.298	0.472
4	16	12	57.001	-21.782	20.892	0.612
5	12	8	51.094	-16.357	15.954	0.742
6	12	12	54.756	-17.624	17.025	0.603
7	14	12	57.024	-20.264	19.785	0.483
8	14	8	53.894	-18.486	18.756	0.609
9	12	10	53.102	-18.089	18.121	0.615

4. CONCLUSION

Fuzzy logic provides an alternative way to represent linguistic and subjective attributes of the real world in computing it is able to be applied to control systems and other applications in order to improve the efficiency and simplicity of the design process.

Simulation results confirm the prior design and analysis for obtaining the optimal combination of

process parameters for Deep Drawing by using fuzzy optimization. It provides a systematic and efficient methodology for the parametric design with far less effort than would be required for most optimization techniques. Optimal combination of process parameters for deep drawing based on fuzzy which gives accurate influencing parameter are as follows.

Sr. no.	Punch force (Ton)	Blank holding (Bar)	Major strain (%)	Minor Strain (%)	Thickness Reduction (%)	comprehensive output measure (COM)
1	12	8	51.094	-16.357	15.954	0.742

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